REMARKS/ARGUMENTS

Claims 1-16 stand in the present application, claims 1, 3-11 and 13-16 having been amended. Reconsideration and favorable action are respectfully requested in view of the above amendments and the following remarks.

In the Office Action, the Examiner has objected to the Abstract as being of improper format. As noted above, Applicants have amended the Abstract in order to correct the deficiency noted by the Examiner. More particularly, the Abstract now contains less that 150 words. Accordingly, the Examiner's objection to the Abstract is believed to have been overcome.

The Examiner has also rejected claims 13, 14 and 16 under 35 U.S.C. § 101 because the claimed invention is directed to non-statutory subject matter. Applicants respectfully traverse the Examiner's § 101 rejection of these claims.

At the outset, it should be noted that claim 16 has been amended to depend from claim 15 and since claim 15 has not been rejected by the Examiner as being directed to non-statutory subject matter, the rejection of claim 16 in this regard is believed to have been overcome.

In addition, Applicants have amended claim 13 to more clearly recite that a user is provided with the information retrieval tool. Accordingly, claim 13 now complies with the MPEP citation by the Examiner, at the top of page 3 of the Office Action, in that there is a "result in a physical transformation outside the computer for which a practical application in the technological arts is either disclosed in the specification or would have been known to a skilled artisan," i.e., a user having access to an information retrieval

tool for augmenting the browser or search engine capabilities of a personal computer, as disclosed and claimed in the present application.

The Examiner has also rejected claims 13-16 under 35 U.S.C. § 112, first paragraph, as failing to comply with the written description requirement. More particularly, the Examiner states that in independent claims 13 and 15, the claimed subject matter "providing an information retrieval tool output to a user input search criterion using said store of weighted search criteria" is not sufficiently supported by the teaching in the specification. Applicants respectfully traverse the Examiner's § 112, first paragraph, rejection of the claims.

In Figure 1 at block 125, the hardware of the present application is clearly shown and its operation is clearly described with reference, for example, to Figures 2 and 3 and the present specification from page 7, line 23 through page 10, line 24. Indeed, block 335 of the flow chart shown in Figure 3 states "Present Identified Query Term relationships to user." Moreover, since claims 13 and 15 have <u>both</u> been amended to more clearly recite that <u>a user</u> is provided with the information retrieval tool output, it is respectfully submitted that claims 13 and 15 and their respective dependent claims 14 and 16 are fully supported by the present specification in the Figures and text portions identified above. Accordingly, Applicants respectfully request that the Examiner withdraw the § 112, first paragraph rejection of these claims.

The Examiner has also rejected claims 14 and 16 under 35 U.S.C. § 112, second paragraph, as being indefinite for failing to particularly point out and distinctly claim the subject matter which Applicants regard as the invention. Applicants respectfully traverse the rejection.

In explaining this rejection, the Examiner has improperly parsed portions of the claims and first alleges that the word "thresholded" is not a recognized word in the dictionary. The Examiner does not indicate which dictionary she consulted, but Applicants respectfully submit that the term "thresholded" is well known by those of ordinary skill in the art of computers, software and imaging. More particularly, the Examiner is invited to "Google™" the term "thresholded" which will locate a plethora of technical documents using that term in substantially the same way it has been used with respect to these claims, i.e., the verb form of the noun, threshold. For the Examiner's convenience a sampling of four such documents obtained by "Googling™" the term "thresholded" are attached hereto. The titles of the articles are:

1. "Uncertainty in Artificial Intelligence" (1996);
2. "Error Bounds for Voting Classifier Using Margin Cost Functions" (February 24-26, 1999);
3. "Fuzzy Definition of a Thresholded Coherent Structure" (March 28, 1995); and
4. "Reading a Binary 3D Thresholded Data Set" (June 22, 1999).

Accordingly, the Examiner is in error when she states that the term "thresholded" is not a recognized word. Moreover, the term "binary thresholded" is clearly disclosed in the specification at page 12, line 15 through page 13, line 9.

Finally, the Examiner states that the term "applicability" is too broad in scope for a person of ordinary skill in the art to understand what applicability the claim language is referring to. Applicants disagree with the Examiner in that the actual term "of

applicability" refers back to the parent claim from which claims 14 and 16, respectively depend. However, in order to expeditiously further the prosecution of this case, Applicants have deleted the offending term "of applicability" from claims 14 and 16. In view of the above-described comments, it is respectfully submitted that the Examiner should withdraw the § 112, second paragraph, rejections of claims 14 and 16.

In rejecting the present claims over previously cited art, the Examiner has issued the same claim rejections as were detailed in the first Office Action dated March 9, 2005. In support of continuing to reject all of the claims over the same previously cited art, the Examiner at pages 18-21 of the Office Action argues that the features presented by Applicants for patentability in their previous amendment response were not found in the present claims. Accordingly, Applicants have amended independent claims 1, 7, 13 and 15 to correct this deficiency pointed out by the Examiner.

The claims have been amended to more clearly define the novel features therein. Firstly, "search criterion" has been amended to read "query term" and secondly, amendments have been made to more clearly recite that <u>every</u> set of information (document) has a weighting associated with every query term. These amendments are intended to address the issues raised by the Examiner on page 19, last two paragraphs of the Office Action, where the Examiner states that many of the features identified as being novel in the present invention are not explicitly defined in the claims. This amendment now clearly differentiates the present invention from that of Ozawa which relates to "<u>retrieval techniques</u>."

Thus, all of claims 1-16, standing in the present application, are believed to patentably define over the cited art taken wither singly or in any combination. More

particularly, Applicants again assert as they did previously that the Ozawa reference has virtually nothing to do with the present application in that it describes a system that automatically selects an optimal information retrieval technique when multiple information retrieval techniques are available (see page 5, paragraph 1 and page 7, paragraph 7). Thus, it would not have been obvious to combine the references in the manner asserted by the Examiner, but even if the references are combined, Applicants' inventions would not result.

The previous detailed arguments submitted as to why Ozawa is not relevant and pertinent prior art combinable with any references to reject any of the present claims was presented in the previous Amendment dated August 9, 2005 and are hereby incorporated herein by reference.

Therefore, in view of the above amendments and remarks, it is respectfully requested that the application be reconsidered and that all of claims 1-16, standing in the application, be allowed and that the case be passed to issue. If there are any other issues remaining which the Examiner believes could be resolved through either a supplemental response or an Examiner's amendment, the Examiner is respectfully requested to contact the undersigned at the local telephone exchange indicated below.

Respectfully submitted,

NIXON & VANDERHYE P.C.

By: ______________________
Chris Comuntzis
Reg. No. 31,097

CC:lmr
901 North Glebe Road, 11th Floor
Arlington, VA 22203-1808
Telephone: (703) 816-4000
Facsimile: (703) 816-4100

Entailment in Probability of Thresholded Generalizations

Donald Bamber

Abstract:
A nonmonotonic logic of thresholded generalizations is presented. Given propositions A and B from a language L and integer k, the thresholded generalization A=>B{k} means that the conditional probability P(B|A) falls short of one by c*d^k. A two-level probability structure is defined. At the lower level, a model is defined to be a probability function upper level, there is a probability distribution over models. A definition is given of what it means for a collection of th generalizations to entail another thresholded generalization. This nonmonotonic entailment relation, called "entailmei probability", has the feature that its conclusions are "probabilistically trustworthy" meaning that, given true premises improbable that an entailed conclusion would be false. A procedure is presented for ascertaining whether any given c premises entails any given conclusion. It is shown that entailment in probability is closely related to Goldszmidt and I Z^+, thereby demonstrating that the conclusions of System-Z^+ are probabilistically trustworthy.

Keywords: Nonmonotonic reasoning, probabilistic reasoning.

Pages: 57-64

PS Link:

PDF Link:

BibTex:
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TITLE = "Entailment in Probability of Thresholded Generalizations",
BOOKTITLE = "Proceedings of the 12th Annual Conference on Uncertainty in Artificial Intelligence (UAI-96)",
PUBLISHER = "Morgan Kaufmann Publishers",
ADDRESS = "San Francisco, CA",
YEAR = "1996",
PAGES = "57-64"
}

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Error Bounds for Voting Classifiers Using Margin Cost Functions

Llew Mason, Peter L. Bartlett[1] and Jonathan Baxter[1]
Department of Systems Engineering
Research School of Information Sciences and Engineering
Australian National University
Canberra, ACT 0200
Australia
Email: lmason,bartlett,jon@syseng.anu.edu.au

Abstract — **Recent theoretical results have shown that the accuracy of thresholded real-valued functions (such as voting classifiers) is greatly improved if the underlying function has large *margins* on the training data (that is, correct examples are classified well away from the decision boundary). In this paper, we give bounds on the misclassification probability of convex combinations of classifiers in terms of general cost functions of the margin.**

Several recent results[1, 5, 4] give estimates of the accuracy of pattern classifiers that are thresholded real-valued functions, in terms of their *margins* on the training data. The margin of a real-valued function $f : X \to \mathbf{R}$ on a training example $(x, y) \in X \times \{-1, 1\}$ is defined as $yf(x)$, so that the sign of f is correct whenever the margin is positive, and the further the value $f(x)$ is from the threshold at zero, the larger the magnitude of the margin. Results for sigmoid neural networks with small output parameters [1] and convex combinations of classifiers [4] show that the error of these classifiers is no more than the sample average of the function $\mathrm{sgn}(\theta - yf(x))$ (which takes value 1 when the margin is no more than θ and 0 otherwise) plus a complexity penalty term that scales as $1/(\sqrt{n}\theta)$, where n is the amount of training data. Directly minimizing such a cost function is computationally difficult. Neural network learning algorithms and boosting algorithms (see [2]) work to approximately minimize it by minimizing other margin cost functions (quadratic and exponential, respectively).

In this work, we address the questions: what are suitable margin cost functions for convex combinations of classifiers, and how useful are they as error estimates? We show that the following condition on parametrized families of cost functions ensures that they can be used to give error bounds for convex combinations of classifiers. This condition enforces a trade-off between the effective complexity of the convex combination (as measured by a complexity parameter N) and the distance between the margin cost function and the threshold function $\mathrm{sgn}(-yf(x))$.

Definition 1 *A family $\{C_N : N \in \mathbb{N}\}$ of margin cost functions is* B-admissible *for $B \geq 0$ if for all $N \in \mathbb{N}$ there is an interval $Y \subset \mathbb{R}$ of length no more than B and a function $\Psi_N : [-1, 1] \to Y$ that satisfies*

$$\mathrm{sgn}(-\alpha) \leq \mathbf{E}_{Z \sim Q_{N,\alpha}} (\Psi_N(Z)) \leq C_N(\alpha)$$

for all $\alpha \in [-1, 1]$, where $\mathbf{E}_{Z \sim Q_{N,\alpha}}(\cdot)$ denotes the expectation when Z is chosen randomly as $Z = (1/N) \sum_{i=1}^{N} Z_i$ with $Z_i \in \{-1, 1\}$ and $\Pr(Z_i = 1) = (1 + \alpha)/2$.

Theorem 2 *For any B-admissible family $\{C_N : N \in \mathbb{N}\}$ of margin cost functions, any finite class $H \subseteq \{\pm 1\}^X$ of classifiers and any probability distribution P on $X \times \{-1, 1\}$, with probability at least $1 - \delta$ over a random sample S of n labelled examples chosen according to P, every N and every f in the convex hull of H has $\Pr(\mathrm{sgn}(f(x)) \neq y)$ no more than*

$$\frac{1}{n} \sum_{(x,y) \in S} C_N(yf(x)) + \sqrt{\frac{B^2}{2n} (N \ln |H| + \ln(N(N+1)/\delta))}.$$

We omit the proof (see [3]). A similar result applies for infinite classes H with finite VC-dimension. (Ignoring constant factors, $\mathrm{VCdim}(H) \log n$ replaces $\ln |H|$.) The theorem suggests the use of algorithms that minimize the sample average of these margin cost functions. Experimental results described in [3] show that this approach can have advantages over other algorithms for voting classifiers.

Acknowledgements

Thanks to Yoav Freund, Wee Sun Lee and Rob Schapire for helpful comments and suggestions.

References

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[2] Y. Freund and R. E. Schapire. "A decision-theoretic generalization of on-line learning and an application to boosting." *J. Comp. Syst. Sci.*, 55(1):119–139, 1997.

[3] L. Mason, P. L. Bartlett, and J. Baxter. "Direct optimization of margins improves generalization in combined classifiers." Tech. report, ANU, 1998. (Available from http://wwwsyseng.anu.edu.au/~lmason/doom.ps. See also *Neural Information Processing Systems 11*).

[4] R. E. Schapire, Y. Freund, P. L. Bartlett, and W. S. Lee. "Boosting the margin: a new explanation for the effectiveness of voting methods." *Ann. Stat.*, (to appear), 1998.

[5] John Shawe-Taylor, Peter Bartlett, Bob Williamson, and Martin Anthony. "Structural risk minimisation over data-dependent hierarchies." *IEEE Trans. Info. Th.*, 44(5):1926–1940, 1998.

[1] This work supported by the Australian Research Council.

Fuzzy definition of a thresholded coherent structure.

Defining a coherent structure with a certain threshold level is a common method of separating structures. However, when there is noise in the data, the structure of the boundary might be undesirably fine, and that may completely change the boundary even with a small change in the threshold level. A common noise reducing method is data convolution with a certain F filter where the same threshold value is used to define the new smooth coherent structure. The drawback of this method is that it is a global process, necessitating the whole dataset has to be filtered.

Local filtering is an alternative way. Local filtering is done along the boundary line on the already thresholded coherent structure, not on the original dataset. It is easy to compute adjacent filter values using the previous value when the filters have a constant kernel. These filters can be applied on the thresholded $T_t f(\mathbf{x})$ field. The $F_r T_t f(\mathbf{x})$ values are all in the $[0, 1]$ domain. Note, that this is the fuzzy definition of the coherent structure, and not a probability based definition. If the value is not **0** or **1**, it is not known whether a certain point is an element of the coherent structure or not, but it is known that the point has at least **p** percent of the elements of the original coherent structure in its **r** radius neighborhood (see Figure 4, and reference [5,6] on fuzzy sets and smoothness definitions).

We introduce two parameters, **r** filter size and **a** acceptance level, to define the boundary of the smoothed coherent structure. The smoothness of the coherent structure is set by **r**. Changing the **a** acceptance level, the inner part of an original coherent structure can be captured (high acceptance level), or a group of "islands" can be connected into one large coherent structure (low acceptance level). Figure 2 shows the general and Figure 4 the detailed case.

The efficiency of our algorithm lies in the method, how we determine the boundary line of the coherent structure. All boundary points are inner points, with at least one non-inner neighbor. Starting from any boundary point, the next boundary point can be found by checking the 8-neighborhood of this point in a clockwise direction. The new filter values are always computed at adjacent locations, which has less computational need, as stated earlier. When the whole boundary is traced this way, a chain of the boundary points will compose a closed line.

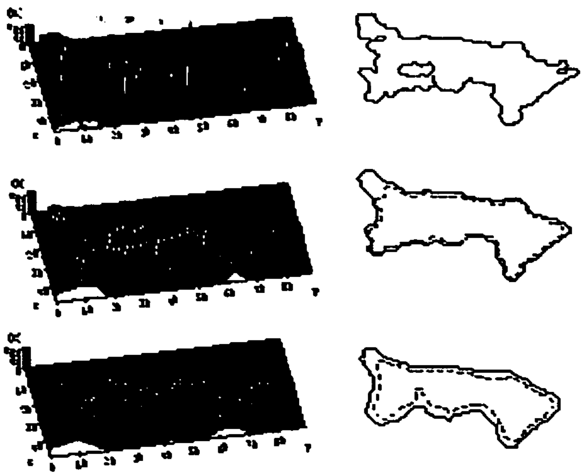

Figure 4: Fuzzy definition of coherent structures with different **r** smoothing kernel sizes, and different a acceptance level. **(a)** The extreme case with **r=1** kernel size gives the original $T_t f(\mathbf{x})$ thresholded

coherent structure. Any acceptance level defines the same coherent structure. **(b)** Small kernel size (**r=5**) keeps details of the original structure. Solid line shows the boundary at $a = 0.5$ acceptance level. Higher acceptance level ($a = 0.8$) defines smaller structure, drawd by dashed-line. **(c)** Large kernel size (**r=11**) smooths the boundary of the structure. The main parts are still visible, and the orientation of the coherent structure is similar to the original orientation. Solid line boundary is at $a = 0.5$ acceptance level, dashed-line represents the $a = 0.8$ acceptance level.

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[x] next [x] up [x] previous

Next: Boundary and line **Up:** Local smoothing along **Previous:** Definitions

---

Akos &
Tue Mar 28 17:04:10 EST 1995

Reading a binary 3D thresholded data set

Lisa Sobierajski Avila lisa.avila at kitware.com
Tue Jun 22 10:26:55 EDT 1999

- Previous message: Reading a binary 3D thresholded data set
- Next message: How to use vtkImplicitDataSet?
- **Messages sorted by:** [date] [thread] [subject] [author]

```
Hello Steve,

Try looking at vtkSLCReader - it reads a run-length encoded 3D array of
bytes from disk.

Lisa

At 03:35 PM 6/21/99 -0600, you wrote:
>
>Hello,
>
>I have a program (written in C) that reads a specialized CT file and
>returns a data array which represents the 3D thresholded data (in order
>of dimension X, then Y, then Z), and the dimensions in XYZ of the 3D
>image.
>
>I'm trying to use the examples in the book to write my own C++ reader of
>the data, but I'm having problems because the examples are focussed more
>at reading multiple 'slices' from MR or CT.  In my case, all the 3D data
>is contained in the data array returned from my C program (for example,
>a data file with a volume of 10x10x10 read with my C program would
>return an array of length 1000, and the dimensions 10,10,10).
>
>Before I begin to attempt to create my own reader to get my data into a
>visualization stream (incorporating my C program), I wanted to see if
>I'm 'on the right track' by using the class vtkVolumeReader as a base.
>If anybody has any suggestions for an appropriate base class that I
>should use for my particular data, or an example that would be useful
>for writing my first own VTKreader, that would be great.
>
>Sincerely,
>
>Steve
>
>
>-----------------------------------------------------------------------
>This is the private VTK discussion list.  Please keep messages on-topic.
>Check the FAQ at: <http://www.automatrix.com/cgi-bin/vtkfaq>
>To UNSUBSCRIBE, send message body containing "unsubscribe vtkusers" to
><majordomo at gsao.med.ge.com>.  For help, send message body containing
>"info vtkusers" to the same address.     Live long and prosper.
>-----------------------------------------------------------------------
>
```

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- Previous message: Reading a binary 3D thresholded data set
- Next message: How to use vtkImplicitDataSet?
- **Messages sorted by:** [date] [thread] [subject] [author]

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